ROBUST DETECTION OF HEART BEATS IN MULTIMODAL DATA USING NEURAL NETWORKS AND BOOSTED TREES

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Abstract

This work describes a novel approach designed for Physionet 2014 Challenge Robust Detection of Heart Beats in Multimodal Data [4]. The objective here is to detect the location of R peaks from the QRS complex. Robust detection of heart beats in a noisy ECG signal is a difficult task. Besides ECG other physiological signals are also recorded at the same time, so the idea here is that if a segment of a signal is noisy, the peaks in that segment can be replaced by peaks found from the other signal if good.

The approach is based on machine learning techniques and makes use of ECG and BP signal inputs. Peaks from each signal are found separately and the best result of the two is chosen in final peak prediction based on short-time variance comparison techniques. The performance of system on the training data is 99.95%. The performance on competition dataset which is hidden for phase I, phase II and phase III respectively are 93.27%, 90.28% and 89.74%. The submission resulted in 1st place in all the three phases of the competition.

Keywords—
ECG, BP, Quadratic spline wavelet filter, Deep learning, Boosted trees

1. Introduction

Manually annotating heartbeat peaks is a cumbersome task and many algorithms have been proposed to locate the peak locations automatically. There are many scholarly papers which use methods like using filter banks, Doppler radars, Support Vector Machine approach etc. and the results have been very good on certain standard ECG datasets and all these techniques are employed on the ECG signals which have been corrupted by standard noises whose effects can be nullified like noise due to baseline wandering, noise introduced by the sensors, power line noises etc.

But when a segment of the ECG signal is significantly corrupted by some random noise, it becomes impossible to detect the location of peaks in that segment and hence it becomes necessary to use the knowledge of peaks located from other physiological signals and in our case it is the BP signal and this forms the problem statement for this paper. An example situation is given for this in the figure Figure.1 where it is shown that a portion of ECG is corrupted by noise and peaks in that segment needs to be replaced with peaks located from the BP signal.

Figure 1. Top: Noisy ECG Signal, Bottom: Clear BP Signal. Figure shows that peaks in the noisy section of ECG can be found considering corresponding BP signal.

Quadratic spline wavelet filter which is quite extensively used for pre-processing the ECG signal is used on both ECG and BP signals to remove high frequency noise as well as artifacts such as baseline wandering. A four level wavelet decomposition of the signal is used as the features to train neural network and boosted tree classifiers for both the signals and peaks are determined from the output of the classifiers and then best of the two signal peaks is selected based on short-time variance comparison techniques.

2. ECG-BP peak detection

In this section a step by step procedure of obtaining peaks from ECG and BP is given along with noise reduction techniques. Both the ECG and BP signals are normalized separately so as to have a zero mean and unit variance and then passed through a quadratic spline filter [1][2][3] to remove noise.

2.1. Quadratic Spline filter

This filtering involves passing the ECG signal through a series of low pass and high pass filters as shown in the Figure 2.

The signals out D1, D2, D3 and D4 are called the 1st detail, 2nd detail etc. respectively. The first pass filter

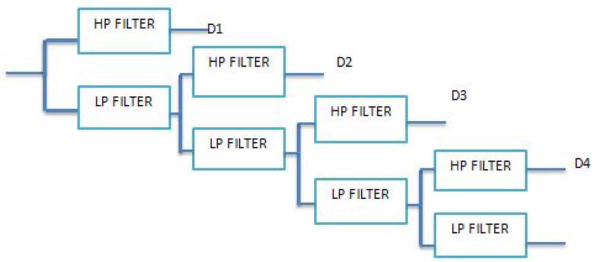

Figure 2. Quadratic Spline Filter

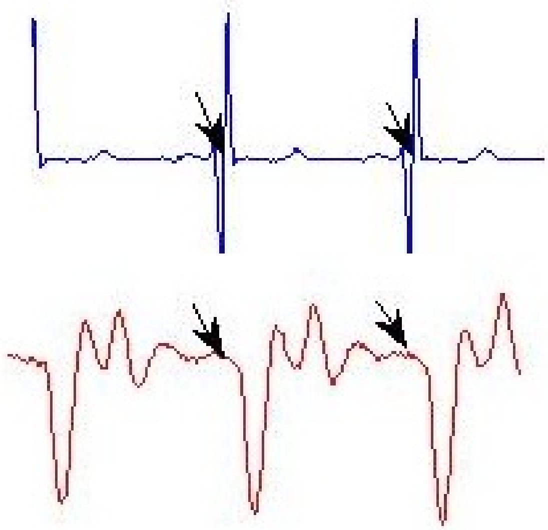

Figure 3. Wavelet Transformed Signals Top: D4 for ECG Bottom: D4 for BP

removes the high frequency noise and the last high pass filter eliminates the baseline wandering problem which is nothing but a low frequency noise. We then consider D4 [Figure 3] and D3 details for training the 2-class classifier using a Neural Network(NN). This kind of filtering works for ECG and BP signals of any sampling frequency though we re-sample the signal to 250 Hz for it to work with the classifiers.

The coefficients for high pass and low pass filter respectively are

$$H = [0.125, 0.375, 0.375, 0.125]$$

$$L = [-2, 2]$$

And the scaling factor lambdas for each stage are

$$Lambda = [1.5, 1.12, 1.03, 1.01, 1.00]$$

2.2. Training Neural Networks

For training the neural network we used the training set provided by the physionet challenge 2014 which contain 100 10-minute excerpts (”records”) of longer multiparameter recordings of human adults, including patients with a wide range of problems as well as healthy volunteers containing both ECG and BP signals.

2.2.1. Training on ECG signal

Each sample of the training data consists of 101 features from the 4th detail and 101 features from the 3rd detail taken together so a total of 202 features. It is a binary classification where the outputs are labeled true for those inputs where the central feature in both D4 and D3 consists of a peak point and the outputs are labeled false otherwise. For the competition We used Deep Learning Tool [5] to train the single layer neural network with dropout functionality and found the optimum value for the number of hidden neurons to be 100 and accuracy with respect to this classification was found to 94%.

2.2.2. Training on BP signal

Similar to ECG but instead of selecting 101 features continuously from both D4 and D3 we select them in an alternate fashion since the samples in BP signal are found to be more correlated than ECG so it considers a segment of 201 samples from both D4 and D3 to construct a sample for neural network. We found 150 to be the optimum value for the single layer neural network with dropout functionality and accuracy with respect to this classification was around 93%.

2.3. Finding Peaks from NN output

Now the main task is to detect peaks from the continuous signals ECG and BP. Since the NN is trained for input signals of frequency 250Hz every signal needs to be resampled to this frequency. Next step is to normalize the signals and apply quadratic spline filter and take out D4 and D3 from it. Then the data is organized for supplying it to classifiers. We check each point on the sign al to be a peak or not by taking it to be the central feature from both D4 and D3 for BP and ECG separately as discussed in the training of NNs. This way each sample of the signal is checked for its possibility of being a peak and hence the output of NN is another vector of the same length as the input signal whose values indicate the probability of the corresponding location or the point being a peak. The output of the NN is shown in Figure 4 for ECG and similar responses are obtained for BP as well and let us call this response as peaks-cluster (PC).

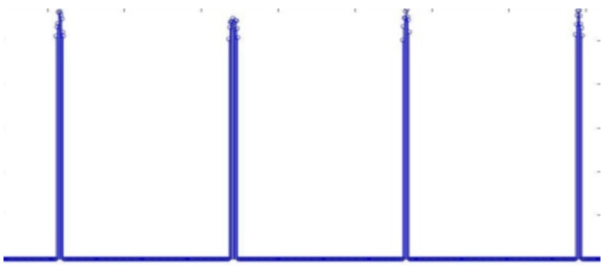

Figure 4. Neural network output for ECG which indicate probability of abscissa being a peak.

The actual peaks now correspond to the local maxima in PC. To detect peaks from PC we use a windowing technique where we use a window of length 60 and slide it along the length of PC to find the local maxima in that region which roughly corresponds to actual peak. In the next stage of post processing we increase the window size based on the average difference calculated between the peaks from the previous results which further eliminate few of the wrongly detected peaks. Finally some simple thresholding is also done to remove extra peaks which are a result of P-peaks being significant in comparison with R-peaks in the signal. All these procedures are separately done on both BP and ECG and resulting two sets of peaks are examined for taking the best result out of them.

2.4. Combining Results

We use short-time variance comparison technique where we take all the peaks corresponding to a certain length of input signal in our case 5000 samples from both BP and ECG and find the variance of the distance between the peaks and the set of peaks with minimum variance is chosen for the final peak set. Extra care is also taken in order to avoid wrong results occurring from the variance technique.

Following up at the end of the competition XGBoost [8] library which implements gradient boosted decision trees(extensively used in Kaggle [9] competitions)was used to train the classifiers. The results even though couldn't be obtained for competition dataset did perform extremely well on the extended data set released by Physionet [4] which contains comparatively very noisy signals, results of which are tabulated in Table 1.

3. Results

The results are tabulated in the Table 1. The Peaks detected are termed as correct if it is detected within a 150ms window on both sides of the actual peak. The percentage accuracy is calculated with respect to the standards set by Physionet Challenge 2014 where the sensitivity (Se) and

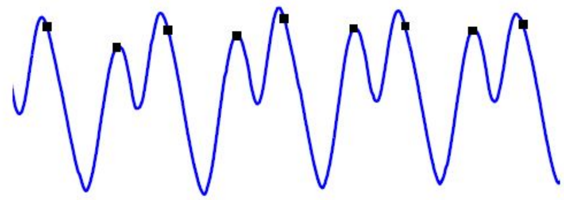

Figure 5. BP signal with double peaks

predictivity (+P) are calculated as follows:

$$Se = \left[100 \cdot \frac{TP}{TP + FN}\right]$$

$$+P = \left[100 \cdot \frac{TP}{TP + FP}\right]$$

Where TP, FN, FP denote true positive, false negative and false positive respectively.

Table 1. Validation results of the proposed algorithms on various datasets. (All measurements are given in %).

	Only ECG		ECG+BP	
Dataset	Se	+P	Se	+P
MIT/BIH	**99.70**	**99.84**	-	-
CinC-2014 Challenge				
Training set	**99.93**	**99.92**	**99.94**	**99.96**
Phase III(300 files)	-	-	**91.63**	**87.86**
Follow-up entry(200 files)	-	-	**95.14**	**90.67**
Using XGBoost [8]				
Training set(100 files)	-	-	**99.95**	**99.96**
Extended set(100 files)	-	-	**96.48**	**92.34**
MIT/BIH	**99.75**	**99.86**	-	-

The algorithm is found to work well when random noise deliberately introduced in one of the signals, in which case the all the peaks in the noisy region would be missing and in the final peaks output will be replaced by the peaks found from the other signal.

The algorithm also does better in situations where there are apparently double peaks in unusual BP signals a situation of which is shown in the Figure 5.

The relatively lower results for the hidden datasets in the challenge were thought of due to the program getting crashed due some unidentified bug in the code.

4. Conclusion

The proposed algorithm gives a better approach in combining the R-peaks obtained by different physiological signals measured at the same time so as to find peaks from unrecoverable signal segments corrupted by noise. The algorithm also proposes novel solution to find R-peaks separately from both ECG and BP signals with very good accuracy on a most of the publicly available standard datasets. The results are found to be improved using XGBoost with minimal complexity in training. Hence can further be improved by carefully analyzing the training data used since noisy training data can impede training performance. Ensembling techniques can also be applied to improve the results.

5. References

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